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A unified health algorithm that teaches itself to improve health outcomes for every individual: How far into the future is it?

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Abstract

The single biggest factor driving health outcomes is patient behavior. The CHR Model (County Health Rankings Model) weights socioeconomic factors, lifestyle behaviors, and physical environment factors collectively at 80% in driving impact on health outcomes, to the 20% weight for access to and quality of clinical care. Commercial determinants of health affect everyone today and unhealthy choices worsen pre-existing economic, social, and racial inequities. Yet there is a disproportionate focus on therapeutic intervention to the exclusion of shaping patient behaviors to improve healthcare. If the recent pandemic taught us a critically important lesson, it is the imperative to look beyond clinical care. According to the Centers for Disease Control and Prevention (CDC), long-standing systemic health and social inequities put various groups of people at higher risk of getting sick and dying from COVID-19, including many racial and ethnic minority groups. The virus was simply more efficient in detecting such vulnerabilities than the guardians of these physiologies. These insights from the pandemic come at the heel of a confluence of three major accelerants that may radically reshape our approaches to hot-spotting vulnerabilities and managing them before they manifest in a derangement or disease. They are the recent strides in behavioral economics and behavior science; advances in remote monitoring and personal health technologies; and developments in artificial intelligence and data sciences. These accelerants allow us to imagine a previously impossible vision—we can now build and maintain a unified health algorithm for every individual that can dynamically track the two interdependent streams of risk, clinical and behavioral.

Keywords

Artificial intelligence, digital health, behavior change, personalized medicine, machine learning, lifestyle change, precision nudging, choice architecture, reinforecment learning

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Unified health algorithm enabling personalized, patient-centric healthcare

While an intelligent decision support system helps the clinician predict, diagnose, and treat a condition, an intelligent behavior support algorithm can help the patient minimize the presentation of such a condition, by engaging in prescribed or preventative health behaviors.[1–3] This algorithm would draw from behavior change theories that offer unifying frameworks to identify key determinants of behavior that may explain and predict how people would engage with their healthcare needs to make health-related decisions. Behavioral theories are infrequently applied to healthcare today and this may explain some of the current challenges with achieving optimal health outcomes for patients. Using adaptive behavior shaping, an algorithm that does not require clinicians to spend added time to

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manage or input data could make a "good enough" assessment of behavior potential (motivation × ability) and trigger a stimulus in the form of a "nudge" directly to a patient.[4] Patient responses would decide whether the nudge is upregulated or downregulated, informing a "learning" algorithm over time instead of requiring a perfect predictive model to initiate intervention. This would also be a quantitative approach rather than of existing models based on clinical or behavioral constructs that are largely subjective and non-computational.

The algorithm would need to synthesize signals from multiple sources to constantly sense changes in risk. To manage that risk (trending systolic pressure, for example) it could pick a series of self-managed interventions for the patient (increase physical activity, or improve adherence to prescribed medication regimen, for example). It would then personalize such actions by breaking them down into easily executable steps to nudge action ("extend your walk by 10 min each day this week"). When needed, it would alert a care team that manages exceptional risk, engaging human coaches, counselors, or care navigators only for exceptions. Now imagine this personal behavior support system is powered using artificial intelligence (AI) that teaches itself to sense changes, both in clinical risk (therapeutic), and in the propensity of the patient to act (behavioral risk) to bend the risk curve.[5,6] It needs to constantly construct precision triggers to shape the desired behaviors using targeted health outcomes as the primary goals.

Drawing from the Fogg Behavior Model,[7] such an algorithm might rely on three factors for shaping behavior changes: a patient's motivation to change, her ability to change, and a trigger that converts intent into action, all coming together at the same time. When the desired behavior does not occur, at least one of those three elements may either be missing or simply out of sync. The essence of this approach is to design choice architectures at the level of an individual patient that presents as an action trigger. In a self-learning environment, it is possible to learn the common cognitive biases that influence the patient's decision at a personal level to help them overcome some, if not all of it through trial and error. It works best via iterative feedback optimizing a patient's preferences over the course of time—the more a patient uses it, the smarter it becomes. Such targeted persuasion based on a patient's motivation and ability improves patient adherence to prescribed care as it allows healthcare to be delivered on the patient's own terms. Furthermore, since healthcare delivery today suffers from the lack of perfect health records, our algorithm can overcome this shortcoming by generating its own empirical data from experiments along the way. Other behavioral change methodologies exist in both research and clinical practice but are not considered here primarily because they do not lend themselves to a computational approach (e.g. scoring for the stages of change in the transtheoretical model).

Putting it to test: The encourage trial[8] to address persistence behaviors in a chronic care setting

We describe two randomized clinical trials (RCTs) that test the concept above, one in a chronic care setting and another acute, with Intermountain Healthcare. Our objective through this approach was to enable better health outcomes for people by building self-efficacy so that they can express as much control as possible in the context of their care. There was also intentional thinking about the desired outcomes, as patient engagement with the App was not necessarily the final goal. Today, 50–60% of patients skip medications, follow-up appointments & treatment protocols.[9–11] The adherence and persistence to statins, for example, is between 50% and 60%.[9–11] This lack of adherence to care plans has a significant cost impact on health systems (a 35% greater risk of CVD-related hospitalizations in patients with coronary artery disease in the statin example).

Using objective measurements of adherence from claims and EHR data, a trial in chronic CVD tested whether targeted behavioral nudges, designed and triggered according to individual motivations and abilities, increased adherence to statin medications, and care plan recommendations.[8] In the trial, 182 participants were split into nudge intervention and control arms. Not only was the adherence to statins 12–16% higher even after 12 months in the nudge group compared to control,[8] but a similar trend was found across other medications as well. An improvement (37%) in the composite of death, myocardial infarction, stroke, and revascularization between the nudge and control groups was also found[8]- an important metric for both patients and payers. While the results in themselves are compelling, what is unique about this RCT is that the guiding intelligence for the entire trial was the unified health algorithm. It delivered a complete patient experience. Using a combination of clinical risk data (IMRS[12]), patient responses to a brief onboarding survey and available data on social determinants based on the patient's reported location,[13] the algorithm built a map of each participant. It then nudged each participant to shape statin adherence behaviors using nudge pathways—the right combination of channel (email, IVR, phone calls, SMS texts), message (behaviorally designed content), timing, and frequencies customized for each participant. Using reinforcement learning, it refined nudge pathways to optimize engagement through direct contact with participants. Limitations of the overall trial are published,[4] but a strength was that the study outcome of medication adherence was measured quantitatively from insurance claims data to calculate the proportion of days covered. The drop-out rate in the year-long study was 1.5% and Net Promoter Scores exceeded 80%.

Expanding the unified health algorithm to address an acute care context

The success of the Encourage Trial led a team in Maternal Fetal Medicine at Intermountain to try the algorithm in a trial designed to prevent pre-term births (PTBs). About half a million births in the US each year are classified pre-term (babies born alive before 37 weeks of pregnancy are completed). “Every day a woman stays pregnant after 24 weeks saves $10,000 in the cost of taking care of the baby” said Dr Branch (then Medical Director of Intermountain Healthcare’s Women and Newborns Clinical Program, the principal investigator of the study). Together with other interventions such as low dose aspirin and progesterone therapy, the trial used the App as the primary channel to deliver nudges, considering both the age group (median 29 years) and corresponding digital savvy of the cohort. Participants typically were on-boarded in the 24th week and stayed on the program through delivery. There were no PTBs <35 weeks’ gestation among those that were in the nudging group, resulting in significant savings in the total cost of care (~USD280–300k) through reduced length of stay in neonatal ICUs for complicated pregnancies. Here again, the ability of the Unified Health Algorithm to orchestrate personalized experiences to each participant, consuming available data (minimal personal health information) and generating behavior data sets to teach itself how best to keep the user engaged, adherent and pregnant till the 37th week, all with minimal human intervention, was demonstrated. It resulted in a drop-out rate of 2% over the entire program, a net promoter score of 86%, and substantial, measurable savings. In a true melding of clinical and behavioral dimensions, it gave us a peek into the future of AI-driven, personalized, patient-centric care that helps patients shape their own health behaviors.

Ensuring equitable access to care—A unified health algorithm for every individual becoming a reality

A unified health algorithm can now begin to complement existing therapeutic interventions to improve health outcomes. This has been brought about by the ability to track markers of critical changes in your socioeconomic context, clinical risks, physical environment, together with the changes in your propensity to modify health behaviors, all in real time. Much like a modern automobile with myriad sensors and CPUs that immersively track the “health” of the car and light up the dashboard with warning signals of likely failure, even calling for assistance before an impending breakdown, this unified health algorithm can accompany an individual on her journey of life, teaching itself to grow “smarter” and more personalized with usage over time. This reinforcement learning-led, behavior-shaping approach allows us to envision a previously impossible North star—we can now build and maintain a self-learning health algorithm for every individual that can constantly track the two interdependent streams of risk: clinical and behavioral.

An intelligent behavior support algorithm that we describe, helps the patient prevent (or minimize the intensity of) such a condition by adhering to their physician’s care plan. It also escalates exceptions to a care team to bend the risk curve before it manifests as a condition for clinical intervention. Perhaps the most counterintuitive aspect is that nudging for six intervention groups—manage activity, diet, stress, environment, social relationships, and stay health informed—covers a wide spectrum of care management from depression to heart disease, from obesity to diabetes. We have seen this demonstrated in the context of two RCTs and in quality improvement programs in large integrated health systems among patients managing diabetes, hypertension, and even behavioral health derangements, making a strong case for a future in which an intelligent health algorithm guides every individual towards their optimal state of health at all times. Other machine learning and discovery-based approaches exist that may produce models of similar value to reinforcement learning. Development of implementations does not depend on the specific model but will require consideration of distinctions found in demographic and behavioral features of different populations.

The unified health algorithm we envisage in this paper essentially keeps track of various markers that signal changes to health risks. The volume, variety and velocity of these markers gathered as inputs for this algorithm could potentially modify the sensitivity of signals if is able to detect changes in health states. This stream of inputs, like most PHI (protected health information), runs the risk of exposure of patient information. While studies cited herein did not use PHI for patient nudging, given these are normalized inputs for consumption by the algorithm, they have a unique advantage in that they can be encrypted and permissioned for use by the owner patient. The perceived risk of exposure can thus be mitigated by technologies that democratize the secure use and application of personal health and behavior data only as permitted by the patient.

Digital health has the power to redefine how we think about care delivery within the context of people’s daily lives and choices. It can do more than alter the site of care—it can evolve the very nature of care by making patients in charge of their own care. Targeted persuasion, if done transparently and with people having the ability to opt-out, can go a long way in improving patient adherence to prescribed care and deliver better health outcomes without an increase in stress levels. The internet is now a viable social science platform to study behaviors across massive global populations.[14] With 4.3B internet users worldwide (Jan 2021) and 3.7B active social media users (Jan 2021), it is now possible to use the online/offline activity of the entire internet to infer social science insights.[14] We are beginning to see a plethora of transdisciplinary studies that span behavior science, data science, and social technologies. Algorithms are already pervasive in assessing lifestyle behaviors and risks.[15–18] They now segment and estimate sleep durations using clinical-grade sensors, use heart rate variability signals (derived from electrocardiograms) for the non-invasive detection of diabetes, etc.[15,16] We are beginning an era of care delivery where the progression of these algorithms is towards the consumption of signals that go from reference diagnostics and known chemical markers to social phenotypes that health conditions seem to shape.[19,20] If the ownership and custody of such a unified health algorithm is with an individual and not any one stakeholder, this could be dropped into any open-source network promoting collaboration amongst stakeholders, reducing wastage from overlapping tasks, and opening the gateway for collaboration amongst all players within the arena. The outcome of this could be truly transformational!

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